QASem Parsing

Text-to-text Modeling of QA-based Semantics

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(1) Overview

Semantic representations enable applications to understand, process and generate natural language.
QASem is an evolving paradigm which captures semantic relations with natural-language question-answer pairs.

Both were shot in the confrontation with police and have been recovering in hospital since the attack.

QA-SRL → *Who shot someone? police*

QANom → *What did someone confront with? police*

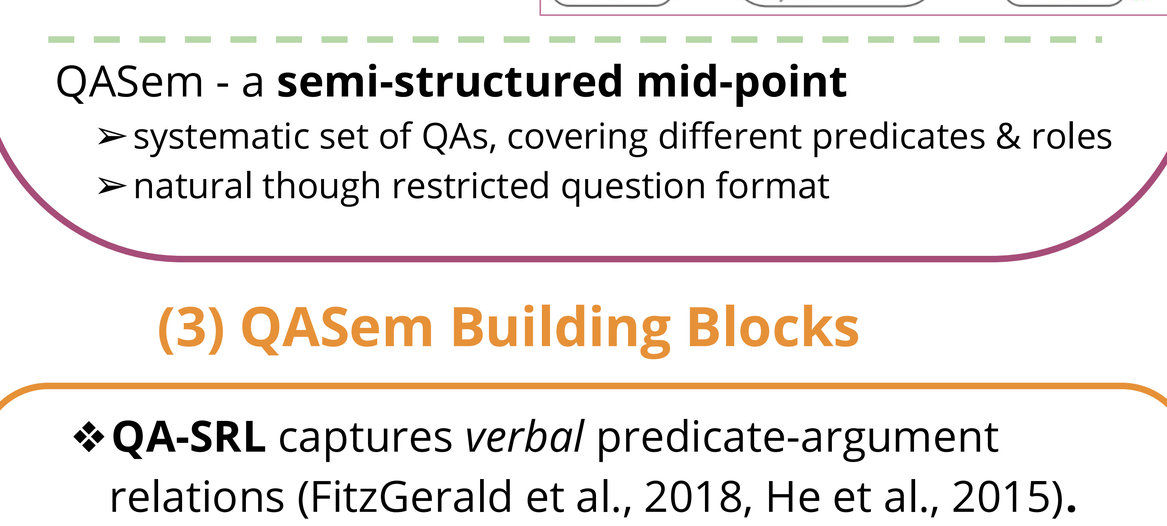
QADiscourse → *Since when have both been recovering in the hospital? since the attack*

We release a unified **QASem tool** based on a seq2seq model, easily applicable for downstream tasks.

(2) Background

Complex tasks require **semantic representations** to exert control over textual information units -
decompose; *manipulate*; *align*; *merge*; etc.

Common representations are highly **structured**

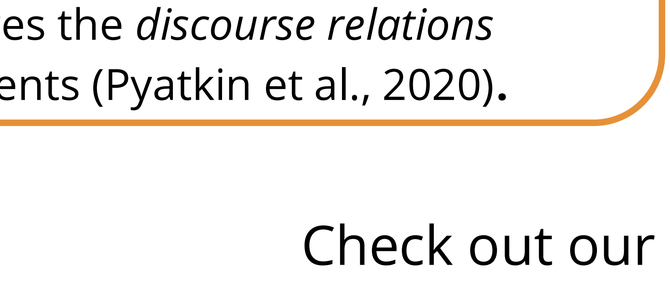


Other popular representations are based on **natural-language** with minimal structure

Open Information Extraction

(Obama, Born, in Hawaii, in 1961)

Summary Evaluation using **QA** (E.g. Wang et. al., 2020)



QASem - a **semi-structured mid-point**
- ➢ systematic set of QAs, covering different predicates & roles
- ➢ natural though restricted question format

(3) QASem Building Blocks

- ❖ **QA-SRL** captures *verbal* predicate-argument relations (FitzGerald et al., 2018, He et al., 2015).
- ❖ **QANOM** captures predicate-argument relations of *nominalizations* (Klein et al., 2020).
- ❖ **QADiscourse** captures the *discourse relations* between two statements (Pyatkin et al., 2020).

(4) Modeling

We fine-tune T5 models to generate a set of question-answer pairs per predicate/sentence.

Input *parse: Both were shot in the [PREDICATE] confrontation [PREDICATE] with police ... [SEP] confront*

Output *Q,A1,A2|Q,A1,A2*

Our models set a new SOTA for the 3 QASem tasks.

Joint QASem learning
QANom dataset is comparatively small.
Joint learning of QASRL and QANom improves QANom parsing.

(5) Effect of Output Linearization

Does the **ordering** of QAs in sequence affect performance?

Can **permutation augmentation** improve results?

		QA-SRL Full			QA-SRL Small			QANom		
		P	R	F1	P	R	F1	P	R	F1
Random-Order	**UA**	74.1	58.6	65.5	65.4	60.0	62.6	65.0	52.1	57.9
	LA	61.6	48.7	54.4	50.3	46.1	48.1	45.1	36.1	40.1
Role-Order	**UA**	76.3	64.4	**69.9**	68.4	59.1	63.4	61.3	56.8	58.9
	LA	63.7	53.8	**58.4**	52.0	45.0	48.2	43.1	39.9	41.4
Answer-Order	**UA**	74.7	63.8	68.8	69.6	58.4	**63.5**	65.6	53.6	59.0
	LA	62.5	53.3	57.6	53.4	44.9	48.8	45.7	37.3	41.1
All-Permutations	**UA**	63.1	64.8	64.0	66.1	59.1	62.4	62.7	53.6	57.8
	LA	51.0	52.3	51.6	52.9	47.3	**50.0**	44.3	37.8	40.8
Fixed-Permutations	**UA**	75.2	60.0	66.7	65.8	58.3	61.8	62.0	52.8	57.1
	LA	62.2	49.6	55.2	50.6	44.8	47.6	44.4	37.9	40.9
Linear-Permutations	**UA**	72.5	62.8	67.3	64.3	60.0	62.1	61.5	57.0	**59.2**
	LA	60.9	52.7	56.5	50.5	47.1	48.8	43.1	40.0	**41.5**

★ Consistent order (Role / Answer) is better than random

★ Augmentation is beneficial when training size is small

Check out our preprint and demo

https://arxiv.org/abs/2205.11413

https://huggingface.co/spaces/kleinay/qasem-demo